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Climate change induced impact and uncertainty of rice yield of agro-ecological zones of India

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ABSTRACT

An innovative approach of using agro-ecological zones (AEZs), instead of using political boundaries, has been adopted for climate change impact analysis on rice production of India. The analysis has been carried out by using a process-based Crop Simulation Model (CSM)-CERES-Rice fed with improved state of art bias corrected climate projections from eight Global Climate Models (GCMs) for four expected climatic scenarios-Representative Concentration Pathways (RCP 2.6, 4.5, 6.0 and 8.5). Using weather-soil-crop information along with year-wise effect of CO_2 increase assumption for different RCPs as input to the crop model, simulations were performed for the base period (1976–2005) as well as three future periods (2020s: 2006–2035, 2050s: 2036–2065, and 2080s: 2066–2095) for insight understanding of climate change impact on rice yield. Model simulated rice yields of future periods were compared with that of the base period to quantify the climate change impact. Results based on multi-GCM ensemble show expected increase in rice yield of most of the AEZs in RCP 2.6 but as on moving towards RCP 8.5 through RCP 4.5 and 6.0, the positive impact on rice yield in RCP 2.6, in major rice producing zones, is expected to mitigate and lead to the negative impact by 2080s. Large spatio-temporal variability is expected in most of the zones with humongous variability in arid and hilly zones. The overall change in spatial rice yield in India taking all used GCM-RCP combinations in consideration is expected to vary from 1.2 to 8.8%, 0.7 to 12.6% and −2.9 to 17.8% due to the expected climate change in 2020s, 2050s and 2080s, respectively.

1. Introduction

India is the second largest rice producing country after China (Lewandowski, 2015) contributing about 20% of total rice production of the world (FAOSTAT, 2015). Rice production in India varies year to year due to annual rainfall variability. In year 2009–10, country's rice production was decreased by 10.1% due to severe drought in many regions and again increased by 16.8% in year 2011–12 (Suneetha and Kumar, 2013). This annual variation shows that the country's rice production depends on vagaries of monsoon which is getting affected due to climate change in the tropics, the most vulnerable region of the world (Soora et al., 2013). The changing average global temperature, expected to increase roughly by 0.02 °C per year in coming two to three decades (IPCC, 2007) due to increasing atmospheric CO_2 concentration, may significantly affect the rice production with large implications on food security. Though the increased atmospheric CO_2 benefits rice plant in photosynthesis but at the same time causes to increased temperature too which may not be beneficial to grow the crop comfortably in tropical regions like India if the increase is beyond the threshold condition. Along with the changing climate, feeding the ever increasing population is another challenge. Thus, for food security, a holistic approach to nullify both the constraints is required in order to increase the production to satisfy the demand of increasing population (FAO, 2009).

Due to the complex interaction between crop and climatic variables, it is challenging task to project climate change impact on any cropping system (Lobell et al., 2011). Therefore, increasing efforts to investigate the impact of climate change on agriculture are going on at different spatial scales all over the world as well as in India (Nicholls, 1997; Lobell et al., 2006; Meza and Silva, 2009; Thornton et al., 2009; Srivastava et al., 2010; Soora et al., 2013). In India, most of the studies have been carried out based on few locations data taking either user-defined fixed incremental-decremental scenarios (Aggarwal and Mall, 2002; Krishnan et al., 2007; Mall and Aggarwal, 2002; Saseendran et al., 2000) or few coarse-resolution global climate model (GCM) outputs (Krishnan et al., 2007; Matthews et al., 1997; Srivastava et al., 2010). These studies essentially suggest employing more refined

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datasets of climate with a large number of high-resolution GCM outputs, crop phenology, and crop production to improve the understanding of climate change impact on crops by practicing some sturdy approach making the analysis more sophisticated.

Recently, with improved state of the art, refined datasets of climate projections have become available from GCMs for four Representative Concentration Pathways (RCPs: 2.6 4.5, 6.0, and 8.5) (IPCC, 2013). Thus, to make an advancement over previous studies, this study is planned to incorporate not only a few locations but the country-wide geographical region in climate change analysis and a large number of GCM outputs with improved datasets to quantify the impact of climate change on rice yield of agro-ecological zones (AEZs) of India. The studies carried out in India, so far in this field, are usually on the political boundaries (district, state or country) which are not homogeneous in climate, soil type, physiography and length of growing period of crop. This homogeneity could only be achieved in AEZs of India up to some extent as the behaviour of most of the crops in each AEZ remains more or less similar. Similar concept of AEZs has been applied in different countries and regions (Armah et al., 2011; Hochman et al., 2012; Mereu et al., 2015; Seo et al., 2009; Sommer et al., 2013; Xiong et al., 2008; Yu et al., 2012). Keeping these important aspects in mind, the present study is aimed to quantify the climate change impact on rice yield over the AEZs of India.

2. Materials and methods

2.1. Study area

The land surface of India, comprised of 20 AEZs (Gajbhiye and Mandal, 2000), has been taken as study area for this study (Fig. 1). India is a bulk constituent of Indian subcontinent with a total geographical area of 3,287,263 km^2 out of which about 391,100 km^2 is used for *Kharif* (monsoon season) rice cultivation (AGRISTAT, 2015). Each AEZ is as homogeneous as possible in terms of climate, physiography, soil type and length of growing period. Major rice producing areas fall in AEZ-4, 7, 8, 9, 12, 13, 14, 16, 19 and 20. The *Kharif* rice yield of all AEZs has been simulated and used to quantify the impact of climate change.

2.2. Data and methods

2.2.1. Description of CSM-CERES-Rice model of DSSAT

Crop Simulation Model (CSM)-CERES-Rice (v4.5), one of the model integrated in DSSAT (Decision Support System for Agrotechnology

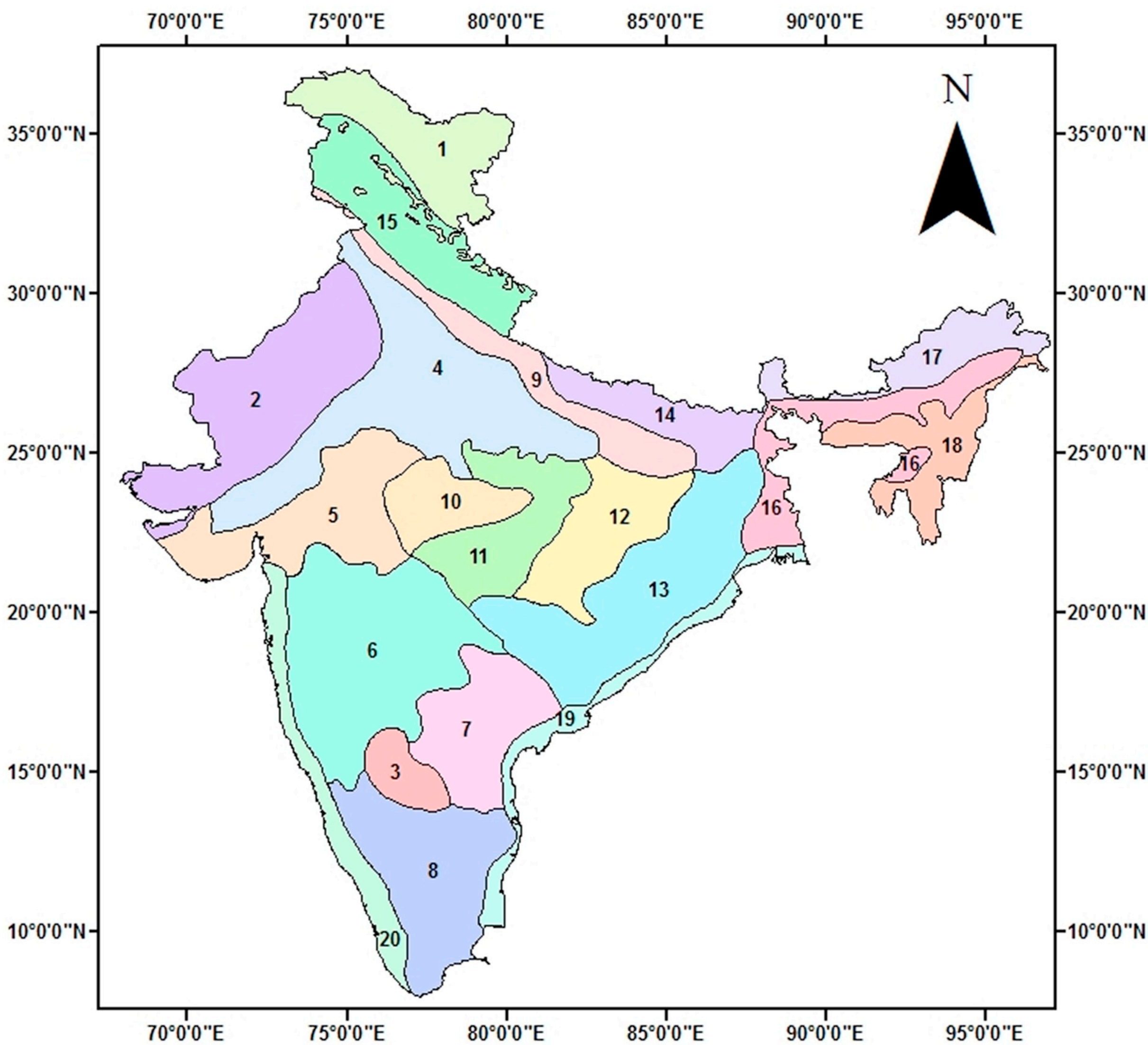

Fig. 1. Index map of study area showing the agro-ecological zones of India.
Source: http://www.nih.ernet.in/rbis/india_information/ecological%20regions.htm.

Table 1
List of abbreviated name, center and atmospheric resolution of used Global Climate Models (GCMs).

Sr. No.	Model	Center	Atmospheric Resolution (lat × lon)
1	BCC CSM1.1	Beijing Climate Center, China Meteorological Administration, China	1.11 × 1.12
2	MRI-CGCM3	Meteorological Research Institute, Japan	1.11 × 1.12
3	GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.0 × 2.5
4	IPSL-CM5A-LR	Institut Pierre Simon Laplace, France	1.9 × 3.75
5	MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 × 2.8
6	MIROC-ESM-CHEM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 × 2.8
7	MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	1.4 × 1.4
8	NorESM1-m	Norwegian Climate Center, Norway	1.9 × 2.5

Transfer) (v4.5) (Hoogenboom et al., 2010; Jones et al., 2003) to simulate the crop yield and growth for decision making and research (Tsuji et al., 1994); is used to analyse the impact of climate change on rice yield.

2.2.2. Processing of input data

Daily observed rainfall and temperature (minimum and maximum) data available from India Meteorological Department (IMD) were collected in $1^\circ \times 1^\circ$ spatial resolution scale for the period 1979–2005. Due to unavailability of observed solar radiation data, the Climate Forecast System Reanalysis (CFSR) dataset generated at $0.3125^\circ \times 0.3125^\circ$ resolution by National Weather Service's National Centers for Environmental Prediction (NCEP) was collected and used after rescaling to $1^\circ \times 1^\circ$ as observed proxy data for the period 1979–2005. Similarly, the daily gridded weather information for same climatic variables generated from eight GCMs, (detailed in Table 1) for base period (1976–2005) and future period (2006–2100) for four plausible emission scenarios (RCPs: 2.6, 4.5, 6.0 and 8.5) were collected from CMIP5 (Coupled Model Inter-comparison Project Phase 5, see Taylor et al. (2012) for detail) data portal (http://cmippcmdi.llnl.gov/cmip5/data_portal.html, accessed 25st May, 2015). The climate change scenarios given by four RCPs- 2.6, 4.5, 6.0 and 8.5 represent greenhouse gas (GHG) emission pathways that can lead to radiative forcing levels in the atmosphere up to 2.6, 4.5, 6.0, and 8.5 W m^{-2}, respectively, by the end of the 21st century (van Vuuren et al., 2011). As it is clear from Table 1 and Fig. 2 (a–d), respectively, that resolutions of newly available improved datasets of GCMs are still variably coarse and biased, the data were bias corrected on daily basis at $1^\circ \times 1^\circ$ resolution using quantile mapping approach described by Ines and Hansen (2006) for rainfall, Li et al. (2010) for temperature and Ceglar and Kajfez-Bogataj (2012) for solar radiation to ease the comparison and ensemble of outputs based on used GCMs. The performance of bias correction for all the climatic variables was tested against the observed dataset for period 1979–2005 (Fig. 2 (e–h)). Large uncertainty in rainfall was observed due to underperformance of two GCMs- IPSL_CM5A_LR and MRI_CGCM3. Rainfall projected by these two GCMs was observed to be significantly low as compared to observed rainfall even after bias correction.

Soil information was collected from FAO (http://swat.tamu.edu/docs/swat/india-dataset/FAO_soils.7z, accessed 20th July, 2015) and spatial soil properties related to moisture content were derived from ROSETTA, pedo-transfer functions (Schaap et al., 2001). Collected soil information was available at 1 km × 1 km scale and therefore rescaled by averaging the same in every $1^\circ \times 1^\circ$ grid to maintain the uniformity in input data.

Simulations were carried out for rain-fed rice cultivar IR36 in monsoon season considering fix transplanting date of 7th July every year in all AEZs. In order to represent the Indian field conditions,

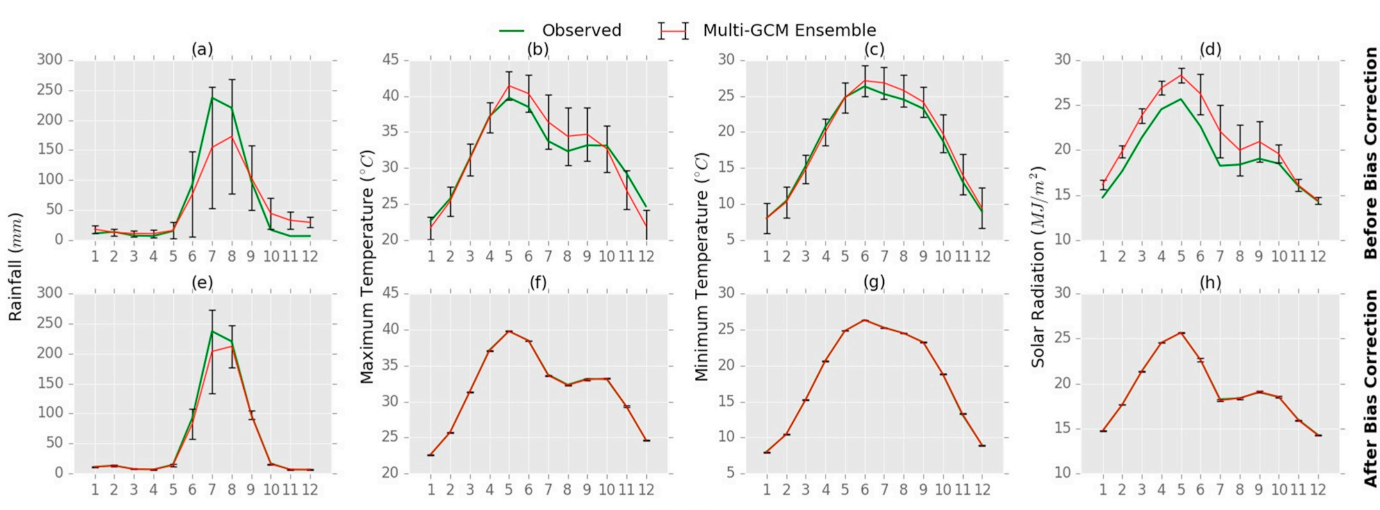

Fig. 2. Comparison between observed and ensemble of multi-GCM weather data of AEZ-4 before bias correction ((a)–(d)) and after bias correction ((e)–(h)) for rainfall ((a), (e)), maximum temperature ((b), (f)), minimum temperature ((c), (g)), and solar radiation ((d), (h)) for period (1979–2005). Error bars depict the variability among the used GCMs.

average fertilization was scheduled by considering urea (46% nitrogen) as a source of nitrogen (N) at the rate of 80 kg-N/ha. 30 kg-N/ha was scheduled at the time of transplanting, 20 kg-N/ha after 25 days of transplanting (tillering stage) and lastly 30 kg-N/ha after 60 days of transplanting (panicle initiation stage). Harvesting was set at the time of maturity in which model itself determines the maturity period based on growing degree days. Though in real practice, these management aspects greatly vary place to place, fixed conditions were chosen all over in India as our objective was to analyse the climate change impact rather than finding out the effects of these on yield.

2.2.3. Projected mean change in climatic variables based on multi-GCM ensemble

Mean change in projected multi-GCM ensemble precipitation, maximum-minimum temperature, and solar radiation of all the AEZs in *Kharif* (monsoon) season, with respect to base period, under RCP 2.6, 4.5, 6.0 and 8.5 scenarios for time period 2006–2035, 2036–2065 and 2066–2095; discussed this point onward as 2020s, 2050s and 2080s scenario, respectively, is shown in Fig. 3. The outcome shows that the precipitation is expected to increase ranging from 3 to 28%, 9–54%, and 14–94% in all the zones by 2020s, 2050s and 2080s under all plausible scenarios, respectively (Fig. 3a). Minimum and maximum

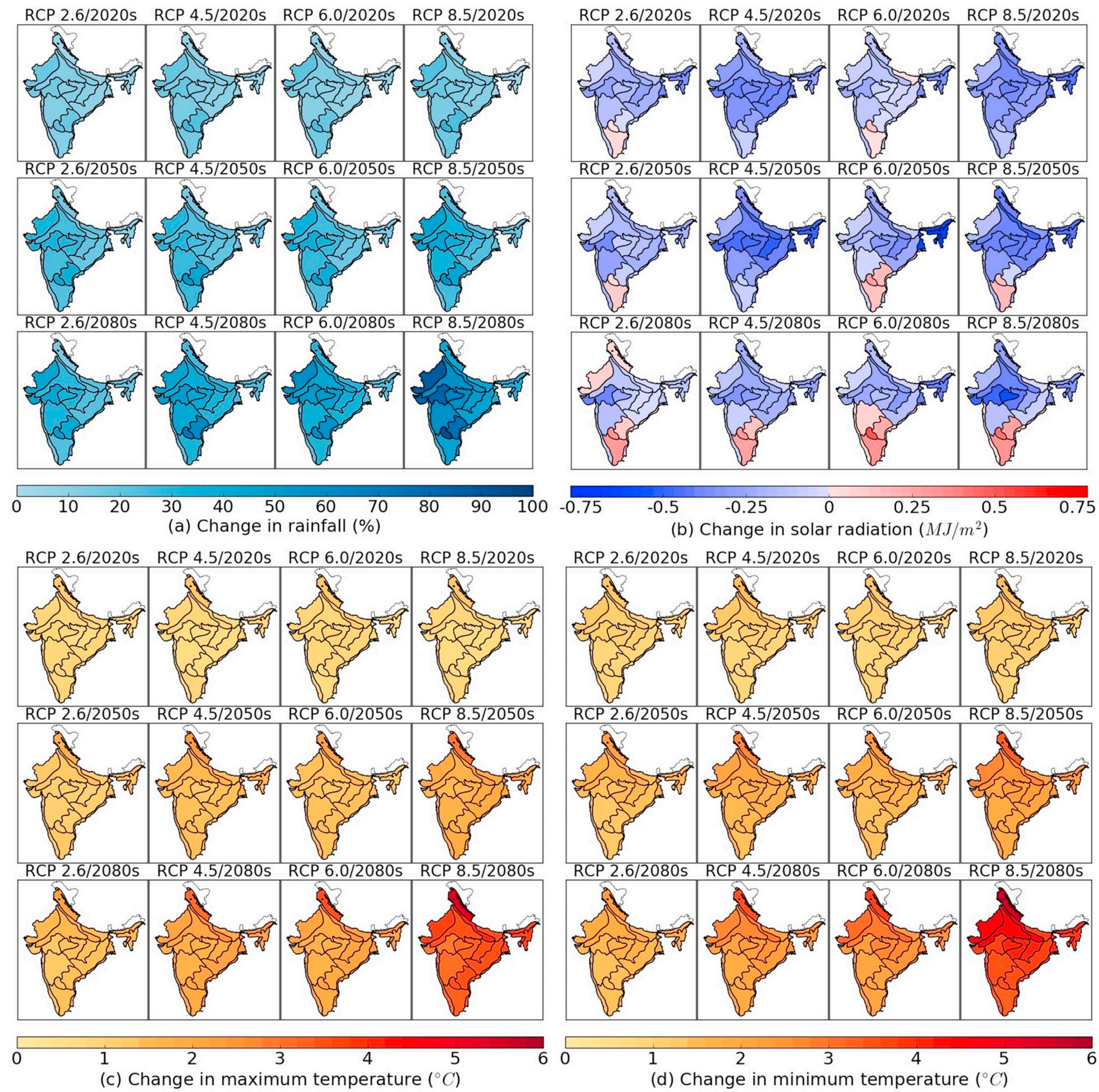

Fig. 3. Seasonal (Jul–Oct) mean change in (a) rainfall, (b) solar radiation, (c) maximum temperature and (d) minimum temperature, with respect to base period, analysed from daily weather data of multi-GCM ensemble for 2020s, 2050s and 2080s under RCP 2.6, 4.5, 6.0 and 8.5 scenarios.

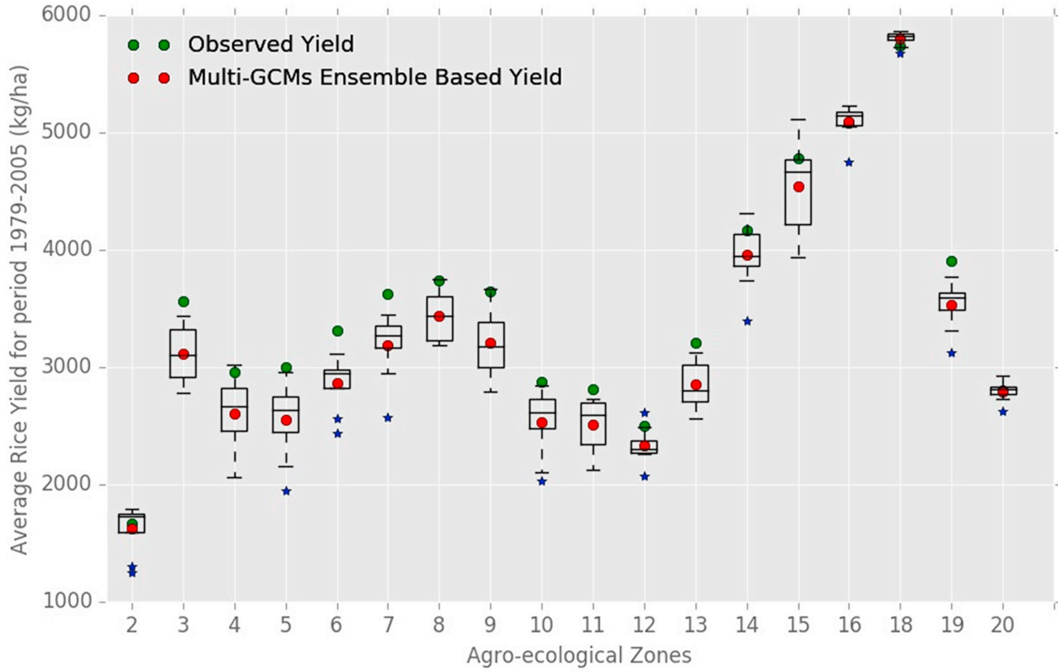

Fig. 4. Comparison between AEZs' average yield simulated from the observed weather data and multi-GCM data used ensemble of rice yield simulated for the period 1979–2005. Box represents the range of rice yield (25th to75th percentile) simulated from all used GCMs. Lines in box and star dots represent the median and extreme yield value (defined as points outside of the width of (First Quartile - 1.5*Interquartile Range) and (Third Quartile +1.5*Interquartile Range)).

temperatures are also expected to increase, respectively, in between 1.2 and 5.7 °C and 1.1–5.3 °C by the end of the 21st century among all the zones under different climatic scenarios (Fig. 3c and d). As incoming solar radiation is directly related to temperature and inversely related to rainfall, the overall impact of both the climate variables shows −0.7 to 0.6 MJ/m^2 change in solar radiation in future (Fig. 3b). In most of the zones, the solar radiation is expected to decrease, may be due to significant and strong inverse correlation between rainfall and solar radiation varying from −0.5 to −0.7 in various AEZs.

2.2.4. Climate change impact estimation

CSM-CERES-Rice was setup and ran by considering weather-soil-crop information dynamically grid by grid (1° × 1°) covering AEZs of India. The model performance was evaluated based on comparison between average yield simulated from the observed historical weather data (1979–2005) with that of multi-GCM used simulated ensemble of yield at AEZ scale for period 1979–2005. After establishing appropriateness of the crop model, future climate change impact on rice yield was analysed by comparing simulated rice yield for 30 years base period (1976–2005) using historical data of all eight GCMs for all the AEZs (covered by 367 number of 1° × 1° grids) with simulated rice yield by using all the eight GCMs for four different RCP scenarios for three future periods of time (2020s, 2050s and 2080s). In this way, about 1,145,040 simulations (30 years × (1 base period × 8 GCMs × 367 grids + 3 future time periods × 4 RCPs × 8 GCMs × 367 grids)) were performed considering increased atmospheric CO_2 concentration into account, which will increase to 421, 538, 670 and 936 ppm by 2100, respectively for RCP 2.6, 4.5, 6.0 and 8.5 (Meinshausen et al., 2011). The grids where base period yield was not simulated, either due to unavailability of data or not getting optimum condition for rice to grow, were not taken into account in climate change impact analysis. The weighted average of yield was calculated for all the AEZs of India for all future as well as one base period. Then the comparison between the base and future period yields at AEZ scale is expressed as percentage change from the base period yields. The same comparison is also performed at grid scale to assess the variability in all AEZs.

3. Results and discussion

3.1. Crop model appropriateness confirmation

India is a large sub-continent with spatially varied soil and climate which make the calibration of crop model quit difficult for each and every part of the country. Also, the main motivation of this study is not to test the model (CSM-CERES-Rice) capability as the model has been used (calibrated/validated/used for crop yield simulations) for many places in India successfully where researchers established its usability for rice yield simulations (Mall and Aggarwal, 2002; Mishra et al., 2013; Saseendran et al., 2000; Satapathy et al., 2014; Singh et al., 2007, 2016; Sudharsan et al., 2013; Timsina and Humphreys, 2006). However, for examining the appropriateness/efficiency of the model, average yield for period 1979–2005 aggregated at AEZ scale simulated from observed and multi-GCM ensemble of historical yield were compared by using calibrated genotype coefficient values from Satapathy et al. (2014) (Fig. 4). On further analysing, high spatial Pearson's correlation for all AEZs was recorded (varying from 0.89 to 0.99) except for AEZ-10 where the same was found to be 0.62. The reason of relatively low correlation for AEZ-10 may be due to underperformance of two GCMs (IPSL_CM5A_LR and MRI_CGCM3) in predicting rainfall as discussed earlier in Section 2.2.2. These results justify the model's capability of simulating rice yield (IR36 variety) at the AEZ scale quite reasonably and support its use for climate change impact analysis with appropriateness.

3.2. Impact of climate change on gridded-discrete rice yield

Year-wise rice yield of each grid was simulated for all GCM-RCP combinations (32 in number) and averaged for 30 years base period (1976–2005) and three future periods (2020s, 2050s and 2080s) for impact analysis purposes. Table 2 illustrates GCM-RCP combination counts showing climate change impact on future rice yield (increase or decrease) in AEZs with respect to the base period. Discussing the facts periodically, it is clear from the table that most of the GCM-RCP combinations are projecting an increase in rice yield in 2020s in all the

Table 2
GCM-RCP combination counts for projected rice yield change in AEZs.

AEZ	2020s		2050s		2080s	
	N > 0%*	N < 0%	N > 0%	N < 0%	N > 0%	N < 0%
2	31(4)	1	31(7)	1	32(11)	0
3	32	0	32(4)	0	31(9)	1
4	26	6	26	6	18	14(2)
5	32	0	31(2)	1	30(5)	2
6	30	2	32	0	32	0
7	29	3	32	0	29(3)	3
8	28	4	29	3	30	2
9	26	6	17	15	12	20
10	28	4	29	3	29	3(1)
11	29(1)	3	29	3	24	8
12	28	4	23	9	18(1)	14(1)
13	31	1	26	6	23	9
14	22	10	19	13	14	18(2)
15	29	3	31(5)	1	30(10)	2
16	22	10	13	19	12	20
18	20	12	17	15	12	20
19	30	2	28	4	21	11
20	31	1	29(2)	3	32(9)	0

* N > 0% means the number of GCM-RCP combinations projecting yield change > 0%, i.e. increased yield relative to base yield. In the 2020s and AEZ 4, N > 0% is 26 which means that 26 GCM-RCP combinations have projected yield change > 0% and rest of the combinations (32–26 = 6 combinations) have projected yield change below 0%, i.e. decreased yield relative to base yield. Value in brackets are GCM-RCP combinations projecting extreme yield change i.e., > 20 (N > 0%) and less than −20% (N < 0%).

AEZs with respect to the base period. Only in RCP 2.6, yield in AEZ-16 and 18 may experience an ambiguous condition where both the possibilities (positive as well as negative impact) are equally expected (Table 3). To realize the uncertainty in rice yield projections, 95% prediction uncertainty (95PPU) is calculated at the 2.5 and 97.5% levels of the cumulative distribution of relative yield change from the base period and is shown in Fig. 5 for all the AEZs and future time periods. Large uncertainty is observed in the AEZ-2 ranging from approximately −4 to 27% (Fig. 5a).

Mid-term (2050s) climate change impact on rice yield is projected to be increasing yield in almost all the AEZs except AEZ-16 where more than half of the GCM-RCP combinations have projected decrease in yield (Table 2). Yield in relatively more AEZs (AEZ-2, 3, 5, 15 and 20) is projected to increase by > 20% as compared to the number of AEZs in 2020s. Yield in few AEZs (RCP 2.6: AEZ-16 and 18, RCP 6.0 and 8.5: AEZ-16) is expected to decrease in this period as > 4 GCMs (out of 8 GCMs) have showed the negative impact. Few zones (AEZ-9 in all RCPs except RCP 4.5 and AEZ-14, 18 in RCP 6.0) are expected to have ambiguous response (equal possibility of positive and negative impact on yield change) (Table 3). As compared to uncertainty in yield change in 2020s, it is very clear from the Fig. 5b that, overall, a large uncertainty is there in yield change in all AEZs with AEZ-2, 4, 10, 12 and 15 are marked as to possess even larger value. Yield change in AEZ-2 is found to have the maximum uncertainty among all zones and varies from approximately −1 to 48%.

The adverse impact of climate change on larger number of AEZs' yield is expected by the end of 21st century compared to 2020s and 2050s as more than half of GCM-RCP combinations have responded negatively in certain zones (Table 2). Yield in AEZ-9,14 and 18 based, evolved as increasing in 2020s and 2050s, is expected to join the decreasing yield category along with the AEZ-16 (Table 2). Equal possibilities of positive and negative impact on yield have come into picture in different AEZs (AEZ-4, 9, 11, 12, 13, 14 and 19) under different RCPs assumption (Table 3). In RCP 8.5, AEZ-4, 9, 12, 14, 16, 18 and 19 are expected to emerge as highly vulnerable zones by 2080s which are prone to experience an inauspicious part of climate change impact on rice yield. Out of these zones, AEZ-4, 12 and 14 are extremely susceptible to experience yield change below −20% as per as the projections from few studied GCMs. Other RCPs (especially RCP 4.5) in this period of time are also prone to have similar impact of climate change in these particular zones. The uncertainty in yield change is also projected to increase in almost all the AEZs with maximum uncertainty estimated in AEZ-2, 12, 15 and AEZ-20 (approximately 2 to 44%, −24 to 21%, −8 to 39% and 0 to 43%, respectively) showing humongous uncertainty in 2080s yield (Fig. 5c).

On an average, excluding extreme changes in yield (yield changes above 20% and below −20% were assumed to be extremes) in all the zones, the average spatial variation in rice yield change is observed to be increasing, ranging from −4.4 to 14.1%, −6.4 to 14.2% and − 10.1 to 16.4% in 2020s, 2050s and 2080s, respectively. The uncertainty band (2.5th to 97.5th percentile) of changes in rice yield (Fig. 5) projected by GCM-RCP combinations shows clearly that AEZ-2, 12 and 15 are expected to possess large uncertainty in yield change in 2020s which is likely to get even more in magnitude by 2080s. The reason behind high uncertainty in AEZ-2 might be the arid nature of zones (high temperature and low rainfall) where suitable environment to thrive rice well, hardly avails and increasing rainfall and CO_2 concentration might avail the suitable climate in future. AEZ-15 is hilly zone (low temperature and medium rainfall), where increase in all three rice growth friendly climatic factors is projected, thus increased yield, might be the reason of high uncertainty. Changing climate, which remains different in magnitude for different GCM-RCP combination, might also be responsible to further affect the uncertainty in all AEZs along with AEZ-12. All AEZs are observed to have an increasing trend in uncertainty in three periodic scenarios except AEZ-2, 9 and 11 where no trend in uncertainty is detected.

3.3. Average climate change impact on rice yield of different AEZs

To assess the overall uncertainty and to know the probable impact of climate change on rice yield of AEZs, the overall impact in terms of change in rice yield is evaluated based on multi-GCM ensemble of the yield change projected by individual GCM for four climatic scenarios (RCPs) for three future time frames (Fig. 6). Analysing the average impact (climate scenario wise), in low forcing emission scenario (RCP 2.6), the rice yield appears to be increasing during 2020s in almost all the zones except AEZ-16 and 18 with respect to the base period yield. Mostly the yield in zones which are in western (AEZ-5), north-western (AEZ-2), north-eastern (AEZ-4) and middle (AEZ-10) part of India are projected to have an increasing-decreasing trend respectively for 2050s and 2080s compared to 2020s yield with few zones (AEZ-8, 12 and 13) in south-western and middle-eastern part of India showing vice-versa results and rest of the zones are expected to experience a decreasing trend except AEZ-3, 6 and 20. In high emission scenario (RCP 8.5) and time frame 2020s, yield is expected to get increased in all the AEZs. Most of the zones are observed to depict a decreasing trend progressing towards the end of the century with respect to 2020s except few zones (AEZ-7, 8 and 11 with aberrant trend and AEZ-2, 3, 5, 6, 10, 15 and 20 with increasing trend). In the first stabilizing scenario (RCP 4.5), a few less than half of the zones are expected to have a decreasing trend and rest owns an increasing trend except AEZ-5, 8, 10, 13 and 19 which possess an aberrant trend (either increasing-decreasing or decreasing-increasing). In second stabilizing scenario (RCP 6.0), yield in large number of zones show either increasing or aberrant trend with few zones (AEZ-4, 9, 14) holding decreasing trend in yield compared to RCP 4.5.

The temporal yield change, based on different GCMs, has not depicted the similar pattern for any of the AEZ. Hence, multi-GCM ensemble of the projected yield change based on different GCMs might not be able to give clear idea about yield change trend. It could only provide the average estimates of yield change in different climatic scenarios and time frames. It is clear from the Fig. 6 that in 2020s, most of

Table 3
GCM counts for projected rice yield change in AEZs for different RCPs and time periods.

AEZ ID	RCP 2.6						RCP 4.5					
	2020s		2050s		2080s		2020s		2050s		2080s	
	N > 0%*	N < 0%	N > 0%	N < 0%	N > 0%	N < 0%	N > 0%	N < 0%	N > 0%	N < 0%	N > 0%	N < 0%
2	7(1)	1	8(2)	0	8(1)	0	8(1)	0	8(1)	0	8(3)	0
3	8	0	8	0	7(2)	1	8	0	8(2)	0	8(2)	0
4	5	3	7	1	5	3	7	1	7	1	4	4(1)
5	8	0	8(1)	0	6	2	8	0	8(1)	0	8(1)	0
6	7	1	8	0	8	0	8	0	8	0	8	0
7	8	0	8	0	7	1	7	1	8	0	7	1
8	6	2	7	1	7	1	8	0	7	1	8	0
9	5	3	4	4	3	5	8	0	5	3	2	6
10	6	2	7	1	6	2	8	0	8	0	7	1(1)
11	6	2	8	0	4	4	8	0	7	1	6	2
12	6	2	5	3	6	2	7	1	6	2	2	6
13	8	0	5	3	7	1	7	1	6	2	4	4
14	5	3	5	3	4	4	6	2	5	3	3	5
15	7	1	8	0	7	1	7	1	7(1)	1	7(3)	1
16	4	4	2	6	3	5	6	2	5	3	3	5
18	4	4	3	5	3	5	6	2	5	3	3	5
19	8	0	6	2	5	3	8	0	7	1	5	3
20	8	0	7	1	8(1)	0	7	1	8	0	8(1)	0
AEZ ID	**RCP 6.0**						**RCP 8.5**					
	2020s		2050s		2080s		2020s		2050s		2080s	
	N > 0%	N < 0%	N > 0%	N < 0%	N > 0%	N < 0%	N > 0%	N < 0%	N > 0%	N < 0%	N > 0%	N < 0-%
2	8(1)	0	7(2)	1	8(3)	0	8(1)	0	8(2)	0	8(4)	0
3	8	0	8(1)	0	8(3)	0	8	0	8(1)	0	8(2)	0
4	7	1	6	2	6	2	7	1	6	2	3	5(1)
5	8	0	7	1	8(2)	0	8	0	8	0	8(2)	0
6	8	0	8	0	8(2)	0	7	1	8	0	8(1)	0
7	7	1	8	0	8	0	7	1	8	0	7	1
8	8	0	7	1	8	0	6	2	8	0	7	1
9	6	2	4	4	4	4	7	1	4	4	3	5
10	7	1	7	1	8	0	7	1	7	1	8	0
11	8(1)	0	6	2	7	1	7	1	8	0	7	1
12	7	1	6	2	6(1)	2	8	0	6	2	4	4(1)
13	8	0	8	0	7	1	8	0	7	1	5	3
14	5	3	4	4	3	5	6	2	5	3	4	4(2)
15	8	0	8	0	8(4)	0	7	1	8(4)	0	8(3)	0
16	6	2	3	5	3	5	6	2	3	5	3	5
18	5	3	4	4	3	5	5	3	5	3	3	5
19	7	1	8	0	7	1	7	1	7	1	4	4
20	8	0	7(1)	1	8(3)	0	8	0	7(1)	1	8(4)	0

* N > 0% means the number of GCM projecting yield change > 0%, i.e. increased yield relative to base yield. In RCP 2.6, time period 2020s and AEZ 4, N > 0% is 5 which means that 5 GCMs have projected yield change > 0% and rest of the GCMs (8–5 = 3 GCMs) have projected yield change below 0%, i.e. decreased yield relative to base yield. Value in brackets are number of GCMs projecting extreme yield change i.e., > 20 (N > 0%) and less than −20% (N < 0%).

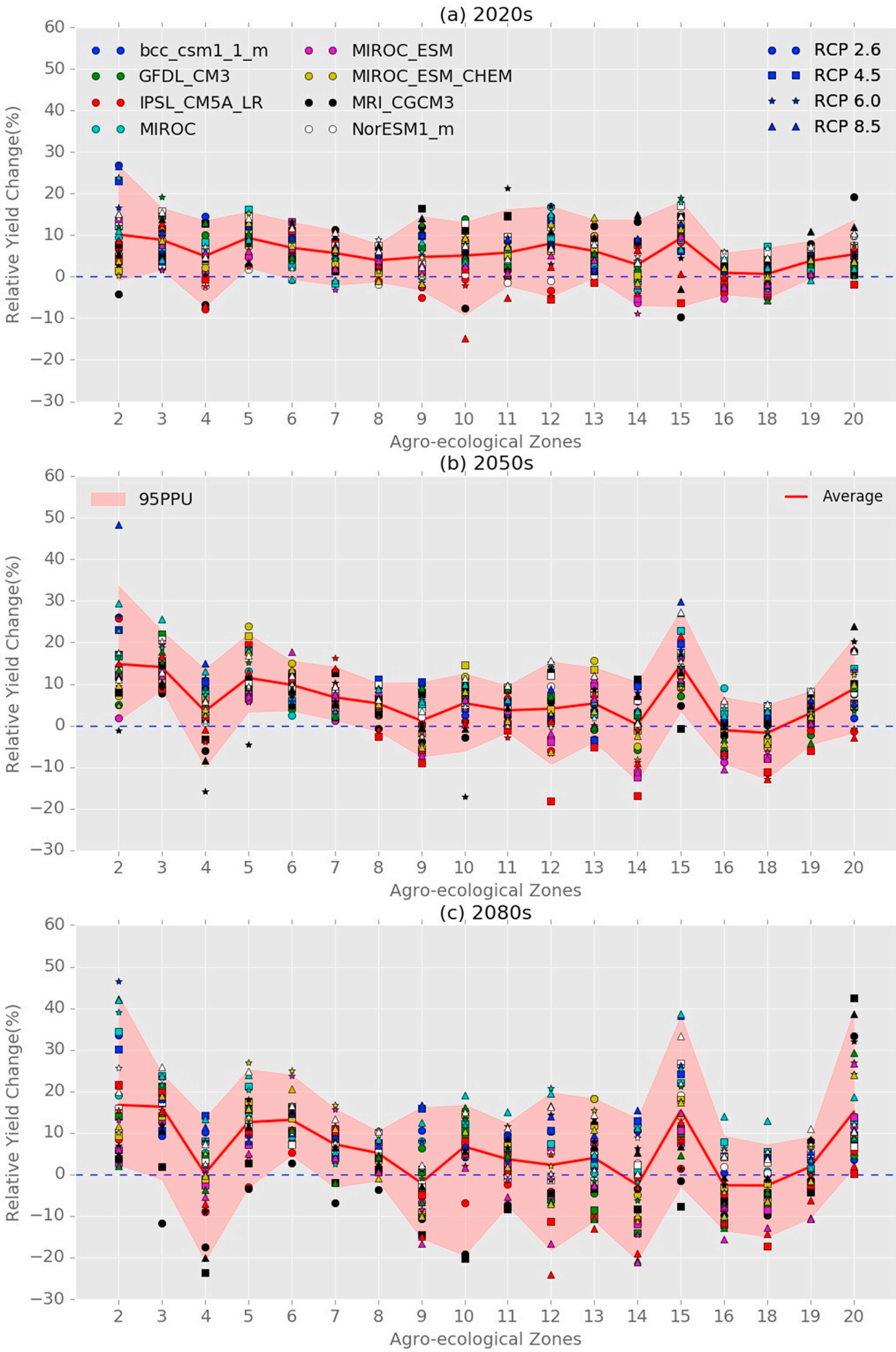

Fig. 5. Climate change impact on rice yield based on GCMs (represented by color dots) for different climatic scenario (represented by dots with different shapes) in (a) 2020s, (b) 2050s and (c) 2080s with respect to base yield (1976–2005). Line in red color represents the average change in rice yield from all the GCMs and climate scenarios. Red color shaded area represents 95% prediction uncertainty. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

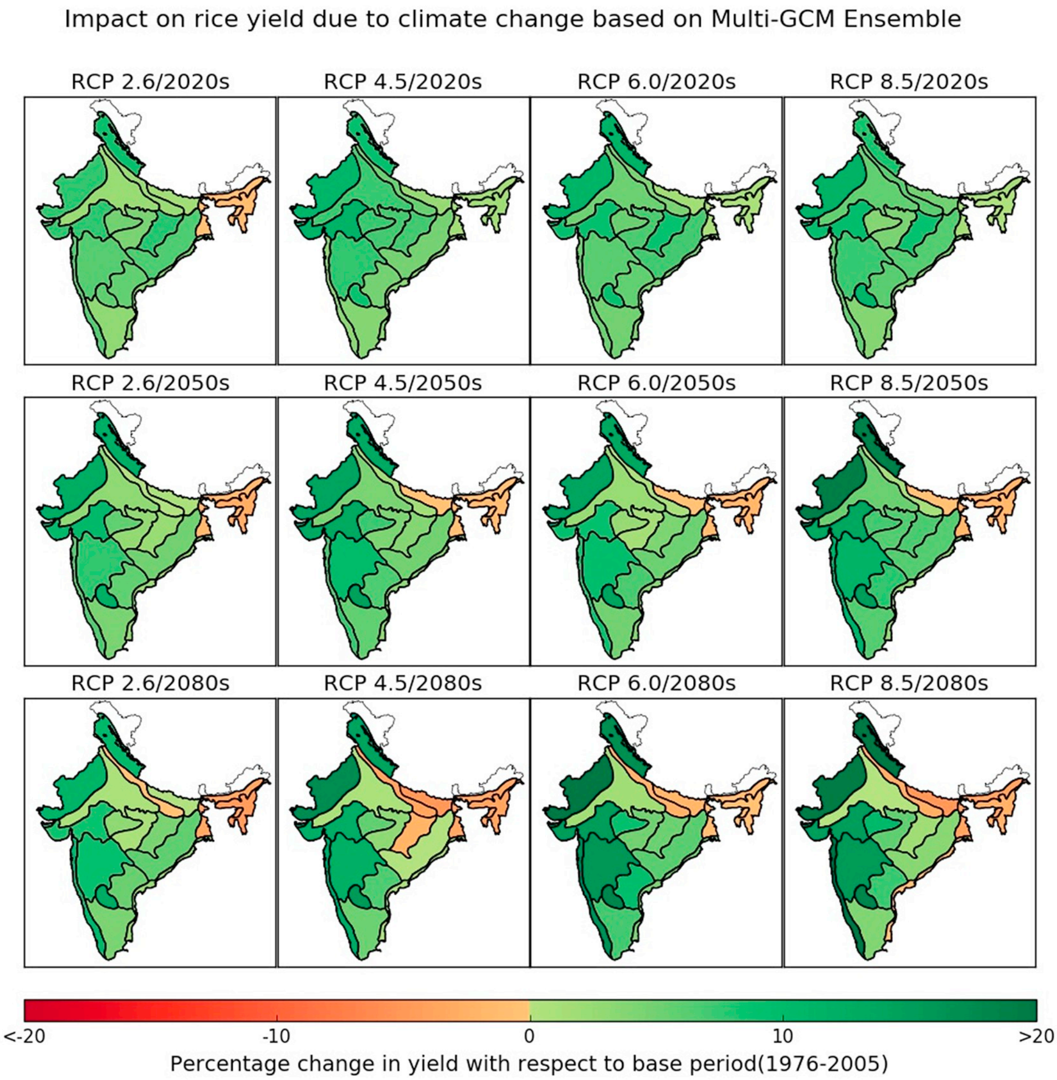

Fig. 6. Percent change in rice yield estimated from ensemble of GCMs with respect to base period yield (1976–2005).

the zones will have positive impact on yield under all climatic scenarios with respect to the base period. The magnitude of positive impact in 2020s is found to be maximum i.e., up to 11.7% in different AEZs which is expected to increase up to 21.0% by 2080s. The negative impact is expected a maximum up to −5.0%. Simultaneous impact of increasing temperature, precipitation and CO_2 concentration has resulted in a negative impact on yield in few zones in high emission scenario (RCP 8.5) in 2080s. Arid zones (AEZ-2 and 3) in north-western and southern, and hilly zone (AEZ-15 and 19) in the north and western-coastal part of India are expected to experience an extreme positive impact (ranging from 5.8 to 11.7% in 2020s which could increase up to 10.3 to 21.0% by 2080s) of climate change on yield. This positive impact in hilly and arid zones may be due to expected temperature and rainfall increment, respectively, along with increasing CO_2 concentration in future which could lead to the possibility of getting a favourable environment for rice cultivation in these zones in future period. Also, due to increasing rainfall and carbon concentration in the atmosphere and resulting increased crop base period vis-à-vis yield in AEZ-2 (arid region), the relative change in yield in future seems to be large and not the yield. Most of the major rice producing zones (AEZ-4, 9, 13, 14, 16 and 19) may experience an increase in yield till 2020s or 2050s, however, yield is expected to decrease by 2080s with respect to 2020s or 2050s which may be even less than the base period yield. Yield in few major rice producing zones (AEZ-7, 8, and 20) is expected to have increasing trend

Table 4
Maximum decrease (Min. (%)) and maximum increase (Max. (%)) (in percentage) in spatial rice yield variability within AEZs.

AEZ ID	2020s		2050s		2080s	
	Min. (%)	Max. (%)	Min. (%)	Max. (%)	Min. (%)	Max. (%)
2	−7.1	33.3	−6.5	37.6	−8.7	39.0
3	2.8	18.0	4.4	25.7	5.8	33.7
4	−5.6	22.4	−4.9	29.0	−13.0	27.1
5	−3.4	22.4	0.0	27.7	−3.6	34.1
6	1.2	18.0	0.8	27.3	1.5	52.6
7	1.4	18.0	−1.1	25.7	−6.3	33.7
8	−2.9	19.4	−3.6	26.0	−13.5	56.7
9	−5.6	10.9	−13.8	22.1	−22.7	30.4
10	1.2	9.8	−0.9	14.2	−2.0	16.9
11	1.2	15.2	−2.8	12.2	−7.1	16.3
12	1.5	15.7	−3.9	15.2	−13.4	19.1
13	−1.7	17.1	−4.9	15.2	−13.4	19.1
14	−1.2	8.7	−4.9	7.1	−12.6	6.6
15	−5.3	54.4	−14.8	98.9	−22.7	108.8
16	−3.2	6.2	−5.6	4.5	−12.6	5.0
18	−3.2	21.2	−5.5	37.5	−7.7	40.0
19	−1.3	10.7	−3.1	12.6	−13.5	12.1
20	−3.4	19.7	−0.3	27.3	−1.2	56.7

in three future period of all the RCP scenarios whereas in AEZ-12 projected yield under RCP 2.6 and 6.0 assumptions possess a mixed behaviour in 2080s. The reason of decreasing yield in major rice producing zones by 2080s may be due to the overwhelming effect of increasing temperature.

3.4. Spatial variability in yield change

The spatial variability in multi-GCM ensemble of yield change within AEZs is estimated as percentage change taking all the RCP scenarios of each period of time into consideration (Table 4). From the Table 4, it is clear that 2 AEZs (Arid: AEZ-2 and Hilly: AEZ-15), as compared to other AEZs, show a large spatial variability (AEZ-2: -7.1 to 33.3% and AEZ-15: -5.3 to 54.4%) in yield change in 2020s. The number of zones with large variability are expected to increase by the end of 21st century. In most of AEZs, except AEZ-15, grids with large spatial variability (particularly with maximum increase in yield change) are observed to have low base period yield. Therefore, the change in yield is evolved as the maximum increase and not the yield itself. The spatial variability of AEZ-15 is expected to range from −22.7 to 108.8% by 2080s. Relatively high yield of few grids within AEZ-15 during base period is expected to further increase due to projected more favourable rice growth conditions in future (increasing rainfall, temperature and atmospheric CO_2 concentration) in this region. Overall, an increasing trend in the spatial variability is observed in all the AEZs in three periodic scenarios.

3.5. Climate change impact on rice yield at country level

The integrated grid-based climate change impact on rice yield has also extended to understand the effect of the same at the country level by combining the results of all the grids and future times, and the results are illustrated in Fig. 7. GCMs projected plausible climate in 2020s, 2050s and 2080s respectively show the effect of climate change on rice yield ranging from 1.2 to 8.8%, 0.7 to 12.6% and −2.9 to 17.8%. In 2020s and 2050s, almost all the GCMs have projected increase in yield. However, in 2080s, most of the GCMs have projected an increase in yield with respect to base period yield as median yield projected by the GCMs is positive in all scenarios. Yield based on few GCMs is projected to be less than base period yield in 2080s. The reason of this may be the increasing temperature in all parts of the country which may be responsible for transforming a positive impact due to increasing rainfall and CO_2 concentration projected by those particular GCMs into a negative impact by 2080s. Decreased yield in a few major rice producing zones and increased yield in rest of the zones is expected to be the reason of overall increased yield at the country level.

4. Summary and conclusion

The climate change impact assessment on rice yield of AEZs of India is performed by using variable climatic conditions and physiographical factors including spatially varying soil properties. Process-based rice growth simulation model CSM-CERES-Rice (v4.5) of DSSAT is used to depict a significant impact of probable climate change on the rice yield of the country in future. Following the fixed fertilization scheme and transplanting date, to represent average rice cultivation condition, the range of *Kharif* season rice yield changes of each AEZ is projected. Based on the low forcing scenario (RCP 2.6) to high emission scenario (RCP 8.5), yield change in most of the AEZs is expected to show a very strange behaviour in the trend either increasing-decreasing or decreasing-increasing, respectively in 2050s and 2080s compared to 2020s. The rice yield in most of the AEZs is expected to increase under RCP 2.6 till the end of 21st century, whereas in RCP 8.5, it is expected to decrease in most of the major rice producing zones with respect to the base period yield. A large temporal and spatial variability in most of the AEZs has come into picture with few zones may have huge variability, may be due to the low base period yield in few grids, therefore, the change seems to be higher than the yield itself. Findings suggest that with time progression from 2020s to 2080s, number of major rice producing AEZs experiencing negative impact of climate change is expected to increase. There is strong probability of increasing rice yield in future in those AEZs which are not the major rice producers like AEZ-2, 5, 6, 15, 20. The impact on rice yield at country level, as projected based on 32 GCM-RCP combinations, may vary from 1.2 to 8.8%, 0.7 to

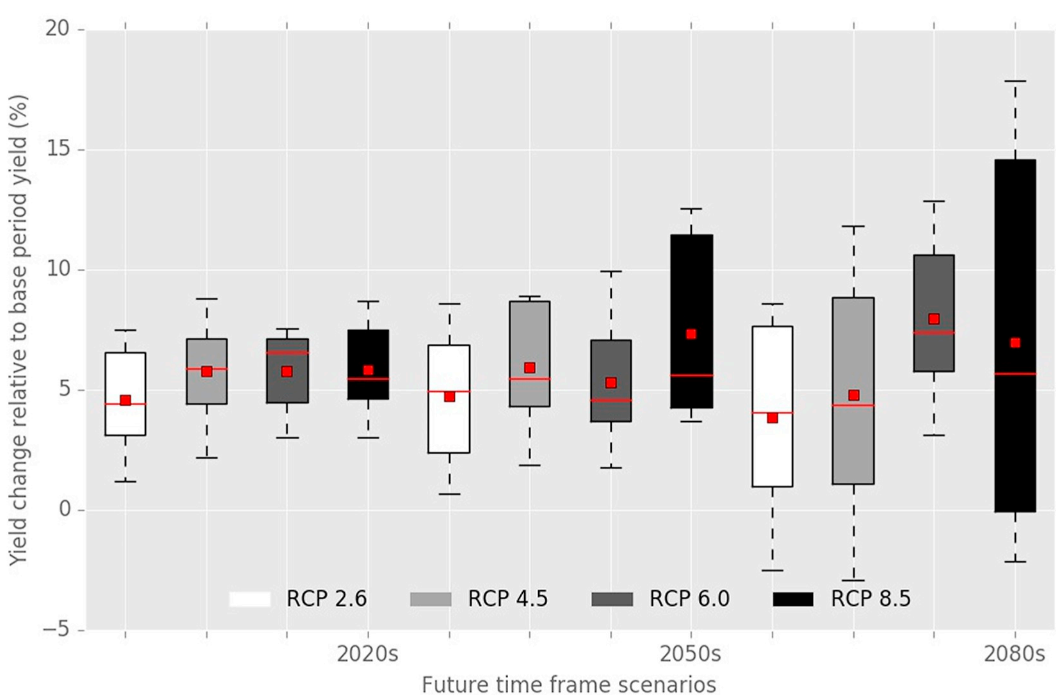

Fig. 7. Range of uncertainty in rice yield change for all the time frames and climate scenarios at the country level. The boxes represent projected change in rice yield from GCMs between the 25th and 75th percentile. The square dot and line in each box represent the mean and the median value of yield change, respectively.

12.6% and −2.9 to 17.8% due to the combined impact of expected change in precipitation and rise in temperature, respectively, in 2020s, 2050s and 2080s.

The investigation performed herein to analyse the climate change impact on rice yield has not incorporated the location specific crop managements like spatially varying transplanting dates and fertilizer applications, incorporation of which may reduce the uncertainty in projected yield change. Another important aspect of future research could be related to economical trade-off among the states of India due to changes in climate. As AEZ crosses different states boundaries, the spatial uncertainty in rice production could further increase due to different climatic conditions in all Indian states. Overall, the outcomes based on different GCMs and scenarios used in this study could be very insightful for deep analysis related to economy and food security to ensure the mitigation of risk on agricultural sector, especially on the staple food such as rice on which globally more than half of the population depends.

Acknowledgement

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